Journal of Theoretical and Applied Information Technology
30th April 2023. Vol.101. No 8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-319

PATTERN RECOGNITION AND CLASSIFICATION OF EEG SIGNALS FOR IDENTIFYING THE HUMAN-SPECIFIC BEHAVIOUR

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ABSTRACT

Analyzing human emotions is a nascent research area that is possible by the analysis of facial expressions in visual, spoken sentences from audio recordings, written content from textual messages, etc. This concept has a vast range of applications, such as monitoring the improvement in psychiatric patients, assisting robots in interacting more intelligently with people, and monitoring signs of attention while driving to enhance driver safety. Information can be aggregated from the emotions communicated through an online platform, including the number of likes and positive or negative reviews that it attracts. To detect the emotion of people for the above application, Electro Encephalogram (EEG) signals are used. Three major emotions of Anger, Sad and Happy can be detected by visualizing the data. All of them are classified depending upon their intensity after transforming the data by Continuous Wavelets. Convolutional Neural Networks are used to train the images generated from the EEG files. The Dataset created is thus trained to later test new signals. In comparison to the other Models, CNN offers better performance since it can do not require several hyperparameters. This is a novel approach of feeding raw EEG signals for Emotion Detection which can be used in multiple fields.

Keywords- *EEG, CNN, Hyperparameters, Human Scientific Behavior, Classification*

1. INTRODUCTION

Computers lack the ability to understand users' emotions, so they often fail to respond to users' needs. Human computer interaction (HCI) aims to improve the interaction between humans and computers. Research into emotion recognition has largely relied on analyzing facial expressions and speech over the past few decades. The problem is that it is easy to change facial expressions or tone of voice, and these signals are not available continuously They differ from using physiological signals that occur continuously and are hard to conceal, such as Galvanic Skin Responses (GSRs), Electrocardiograms (ECGs), Skin Temperatures (STs), and Electroencephalograms (EEGs). EEG represents fluctuations in brain voltage, i.e. the center of emotions. As compared to other models, CNN provides more performance since it does not require a large number of hyperparameters (Deger A et al., 2016). The Mind Bigdata - ImageNet Database from Google holds the EEG signal values of several patients. It holds about 14,000 files on the values of 5 main electrodes as AF3, Af4, T7, T8, Pz. The T7 electrode which is positioned near the Hypothalamus of the brain records the emotions in the human mind. After transformation, the dataset is split into 80% for training and 20% for testing. This is a novel approach to feeding raw EEG signals for Emotion Detection which can be used in multiple fields. We aim to detect the emotions of a human from their EEG signals after thorough analysis done by professionals.

In this digital era where most of the operations are automated and performed by systems, the detailed analysis of the intricate details of an EEG 2 graph is prone to several human errors. In a periodical system, it is easy for people to understand the working of simple machinery. But analyzing EEG

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Signals is not an easy task (Lahat D et al., 2015). Only the highly trained professionals of Neurology and Brain surgeons are equipped with the vast knowledge to understand these signals. Hence, with the growing need for a major number of doctors, the number of errors in the analysis of EEG is not simple. The emotions of a human may seem like a feeble matter. However, with the right usage, it will play a huge role in our physiological lives. Detecting the human emotions with EEG, which can be later developed to aid in psychiatric patient monitoring, is a growing necessity. And so, we found the need to classify emotions with high authenticity. Only the Electroencephalogram signals offer proper authentic values that cannot be faked, unlike the facial monitoring processes by real-time analysis. Hence, we have devised a system that can detect emotions through images of EEG signals.

2. LITERATURE REVIEW

The respiratory belt (RB) signal, the photoplethysmometer signal (PPG), and the fingertip temperature signal (FTT) are used as physiological signals [1]. These signals are used because their collection has become simpler with the advancement of ergonomic wearable technologies. Using the decision level fusion technique, we improved emotion recognition accuracy from 69.86 to 73.08 percent and from 69.53 to 72.18 percent using physiological sources. We demonstrate in these studies that multiple physiological signals can be analyzed and merged to increase the rate of emotion recognition. A study in this report used multimodal physiological signals to recognize emotions, including respiratory belts, photoplethysmography, and fingertip temperature.

According to authors in [2], in order to recognize emotions, it is suggested to use EEG signals, which are further divided into gamma, alpha, beta, and theta frequency bands using discrete wavelet transform subjected to extract the spectral features with respect to the frequency band of principal component analysis. The same process is used in order to extract the features without altering the dimension information in the wavelet transform; if the dimension is not matching, the un-correlated features are mutually transformed. To identify and classify the human emotional behavior state various methods like support vector machine, J-Nearest Neighbour and high demand artificial neural networks are used with the radial basis function using the extracted features of 10 EEG channels with the defined accuracy rate to formulate the better performance with respect to the existing algorithms can be applied to the new dataset specified as DEAP.

Feature extraction and grouping are performed by authors [3] when the general features assigned to the task do not exist in the series of data inputs. In order to deal with this problem, we developed a GRU-based universal deep encoding architecture that can be used to further classify raw EEG datasets. This task will be identified by the host, who will specify the stand-alone data representation with a bounded state for each EEG wave signal. Results obtained from CNN-based and autoencoder networks are compared, thereby allowing different data building structures to be recognized unsupervised under data analysis.

As described in [4], various kinds of human behavior fall under the category of emotion, which can be measured by electroencephalogram (EEG) signals. The purpose of this proposal is to compare the various emotions using discrete wavelet transforms (DWT). We used an induction-based protocol to obtain EEG signals with simulated waveforms. For this emotion recognition experiment, six healthy individuals aged 21-27 years have been used. To classify four emotions (happy, disgust, surprise, and fear) from EEG signals, we used three statistical features (energy and recurrence energy efficiency and RMS) calculated from the signals. This study uses an unsupervised clustering [5] technique called Fuzzy C-Means (FCM) to pinpoint emotions. The results demonstrate that "db4" wavelet transform-based feature extraction combined with the statistical feature could be used to assess the emotions of people from their EEG signals.

The authors [6] used EEG signals in various frequency bands to identify emotions (with assigned channels). The emotional state is classified according to valance and arousal measures checked with combinations of EEG channels. When the DEAP program begins, pre-processed data undergoes normalization. Using a discrete wavelet transform, the obtained EEG signals [7] are then classified into four frequency bands and the entropy and energy are calculated using a K-nearest neighbor classifier. In terms of accuracy, 10 channels, 14 channels, 18 channels, and EEG channels supported the Gamma wave

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-319

band containing 89.54%, 92.28%, 93.72%, and 95.70% within the valence dimension, and 89.81%, 92.24%, 93.69%, and 95.69% within the arousal dimension. Accordingly, the accuracy of determining the gamma band [8] is greatly increased with the increase of channels, resulting in a bigger gamma band than beta, alpha, and theta wavebands.

The authors [9], describe a unique method of estimating spirits using convolutional neural networks (CNN) and deep learning techniques from EEG signals. We use 32 lead EEG signals, which are converted into 2D EEG images using Azimuthal Equidistant Projection (AEP). Following this, the results are sent to CNN based deep neural networks for further classification.

The authors [10] discuss the related EEG-based emotion detection method which is readily available as data with the method of detecting inner emotional states of the brain. This paper [11] proposes a supervised machine learning algorithm to recognize human inner emotions in a two-dimensional model. To identify emotions, we use the EEG signals from DEAP and SEEDIV databases.

A discrete wavelet transform [12] is used as a pre-requisite to pre-process signals in the required 5 bands. Various features including power, energy, differential entropy, and time domain are extracted. Channel wise SVM classifier is promoted and the channel combiner [13] is finished to detect the acceptable emotion/behavior. The classification rate for four classes are 74%, 86% ,72% & 84% for DEAP database and 79%, 76%,77% & 74% for SEED-IV database.

3. PROPOSED SYSTEM

The entire concept of the process is meant to provide educational insight on the emotions of the humans that can be recorded by the EEG signals. The traditional method of identifying emotions is by the detection of facial changes. However, while the non-physiological signals can be easily manipulated, the EEG signals offer high accurate and reliable information on the true emotions of the humans. System design is proposed to satisfy the design requirements. It defines the refined architecture, design rationale. Design requirements should facilitate to form a product prototype with the specification.

It is difficult to look at the EEG signal and identify the state of Human mind. In this, the CNN neural network is trained with MindBigData – Imagenet dataset for prediction. It is evaluated in terms of Sad, Happy and Angry, which are the predicted emotions. The aim of the System Design is to provide the information and data necessary to implement the system elements, complementing the System Architecture. The architecture of the proposed system design is shown in figure 1.

The entire system can be divided into five major modules. These modules are performed in a stepwise manner to enable the smooth transitioning of the program.

1. Generation of Signals
2. Dataset Creation
3. Training the network
4. Parameter Alteration
5. Testing for New Signals

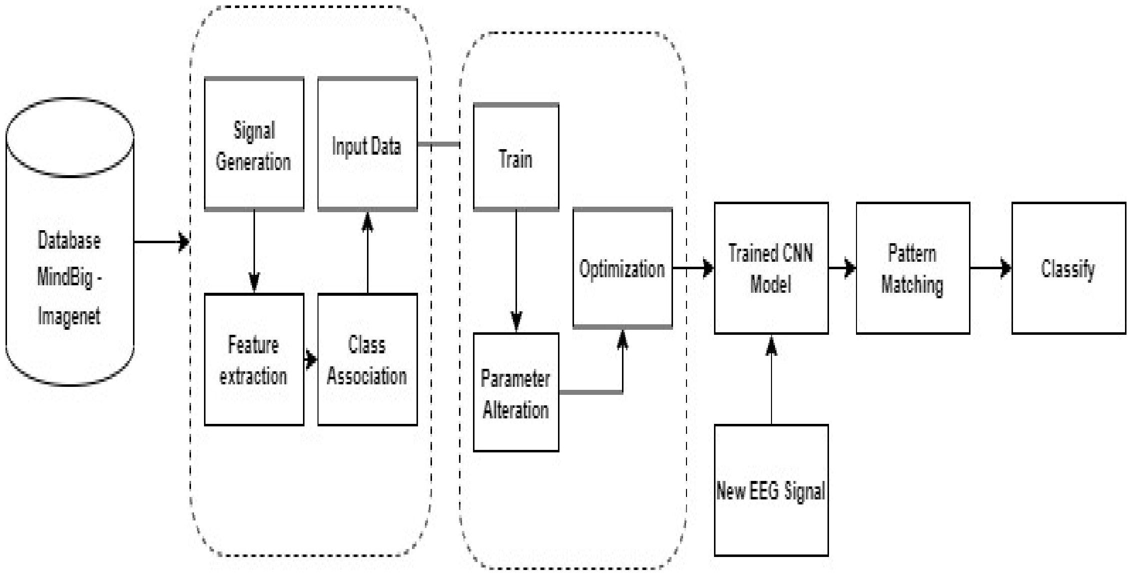

Fig.1. Architecture Diagram.

3.1 Generation of Images

To generate the images which should be trained, the .csv files are converted to images. The csv files are plotted in a graphical structure to generate the signals. This requires the function of All Images from the libraries.

3.2 Dataset Creation

The generated images are labelled with the emotions- Angry, Sad and Happy as their T7 values suggest. The high variance signals depict the 'Angry'; medium variance depict 'Sad' and low variance suggests 'Happy. By using continuous translation and scaling parameters for wavelets, continuous wavelet transforms are a formal (i.e., non-numerical) tool for offering overcomplete visual representations of signals. In this study, we use the Continuous Wavelet Transform (CWT) filter to produce signature images.

3.3 Training the CNN Model

Training a Convolutional Neural Network is necessary before testing data. The CNN used to train the data is "Google Net". Thus, the generated images are trained into the system and then by altering the hyperparameters of the CNN model, accuracy is achieved.

3.4 Parameter Alteration

Some of the parameters that have a direct influence on the training are altered to improve the accuracy of the trained model. By altering the epoch size and learning rate, several training methods were tried and the most accurate one is used.

The learning rate determines how fast the model is adapted to the problem. Here, the rate is set at 1e-4. This was found the most optimum after running a series of other executions with different parameters.

Epochs - Epoch is a common raw dataset representation that can be modified or altered completely according to the machine learning algorithms.

3.5 Testing

The Testing phase consists of feeding raw input signals into the trained CNN model, which can be classified based on their amplitude into the respective emotions – sad or angry or happy. The testing phase is carried out in two separate steps, Multiple and Single.

In multiple testing, all the test cases are executed to find the output of the CSV files together. This is done to get the general idea

Journal of Theoretical and Applied Information Technology
30th April 2023. Vol.101. No 8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-319

of the output. While Single testing is the procedure that is used to feed a raw EEG signal that is untrained, this signal classification is the method of executing a nascent signal and classifying the emotions accordingly.

4. EXPERIMENTS AND DISCUSSION

The system is implemented in MATLAB considering the EEG wavelet transform for the justified emotions happy, sad and angry with limited specification providing constraints to the dataset emulation. Neural schema is generated for every emotion with the observed reading from EEG during the signal transmission without any modulation, so that the obtained results will justify the emotions deduction with nearer accurate values.

4.1 Inputs

The EEG wavelet transformation for happy, sad and angry are shown in the fig 2, 3, 4 and the corresponding wavelet is shown in figure 5.

The inputs were derived and the wavelet transformed EEG signals for different human emotions such as happy, sad and angry etc were stored.

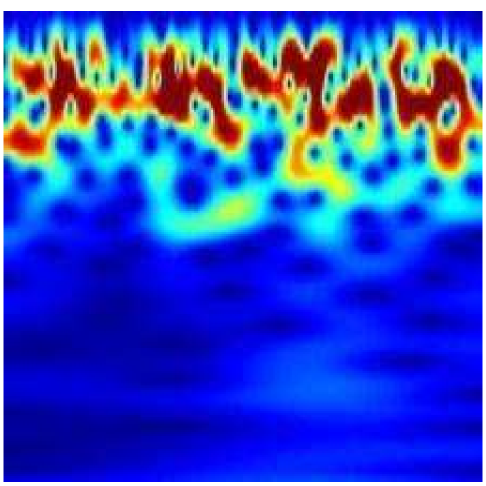

Fig.2. Continuous Wavelet Transform- Happy

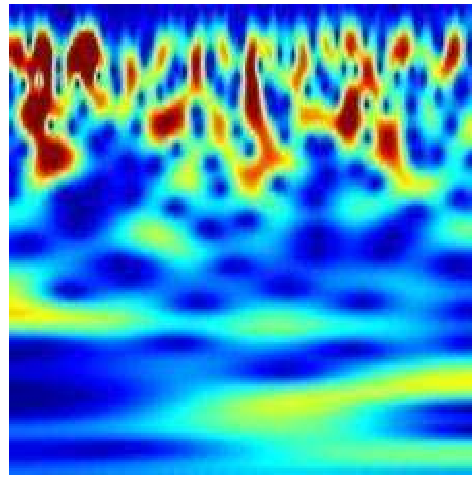

Fig.3. Contipnuous Wavelet Transform- Sad

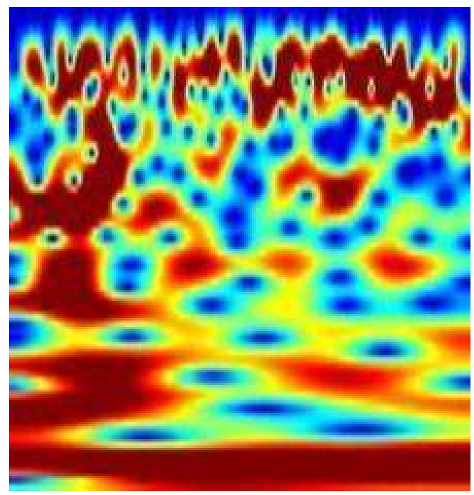

Fig.4. Continuous Wavelet Transform- Angry

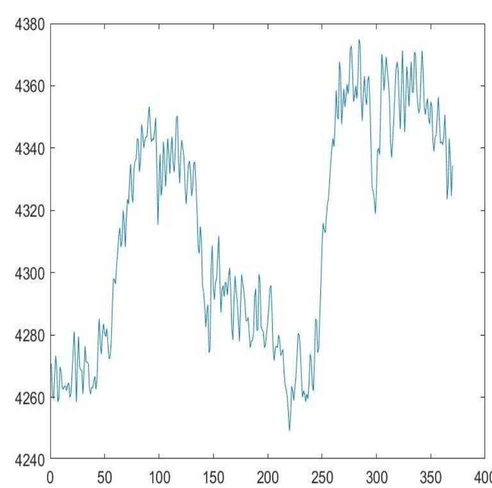

Fig.5. Wavelet Form

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-319

4.2 Training

Neural schema after refined dataset tuned with different EEG waves is shown in the figure 6. The GoogleNet Neural network is trained with the different EEG waves that corresponding to different emotions such as happy , sad and angry etc.

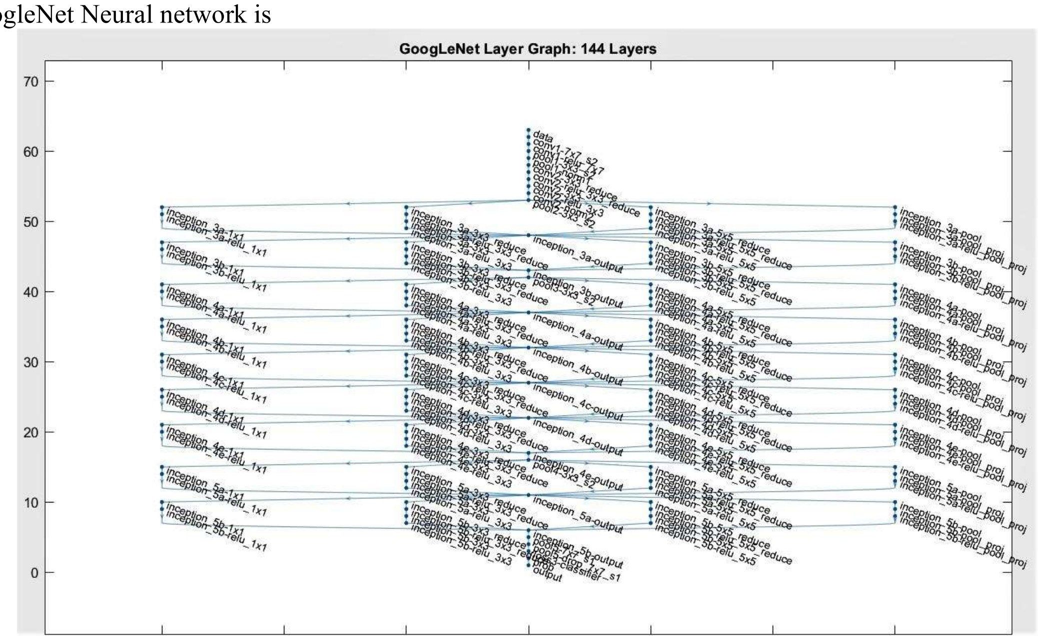

Fig.6. Googlenet Neural Network

The initial training set is shown in figure 7 and the corresponding training output is shown in fig 8. The optimized trained network is shown in figure 9.

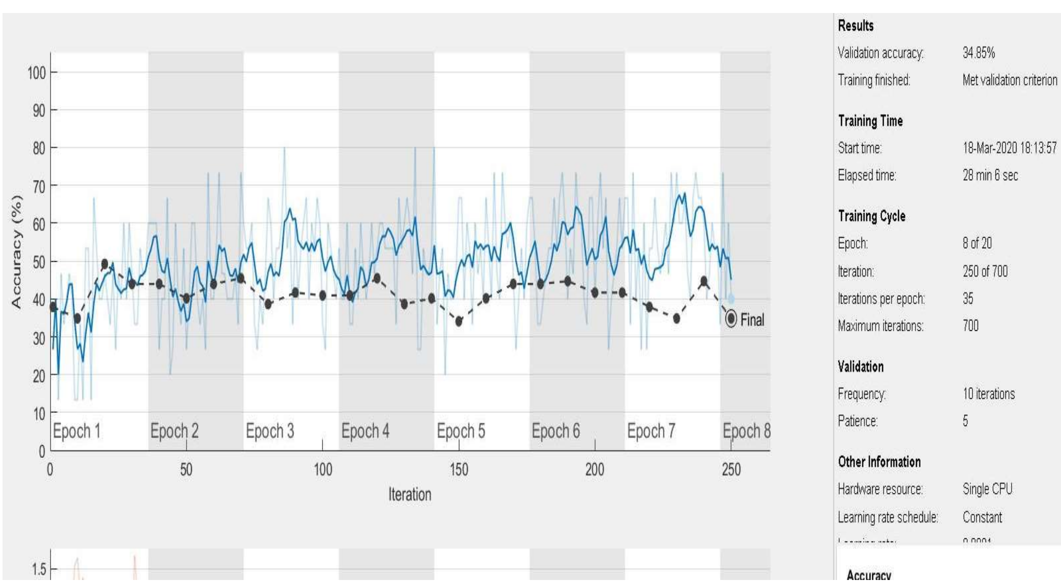

Fig.7.Initial Training Set

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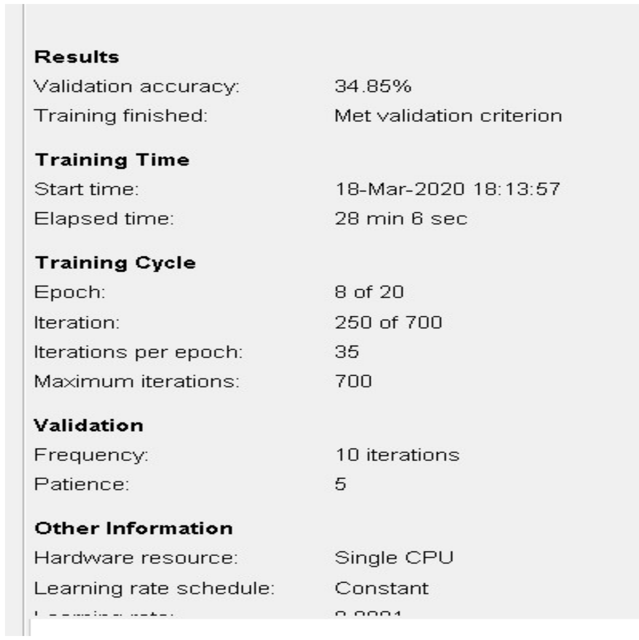

Fig.8. Initial Training Output

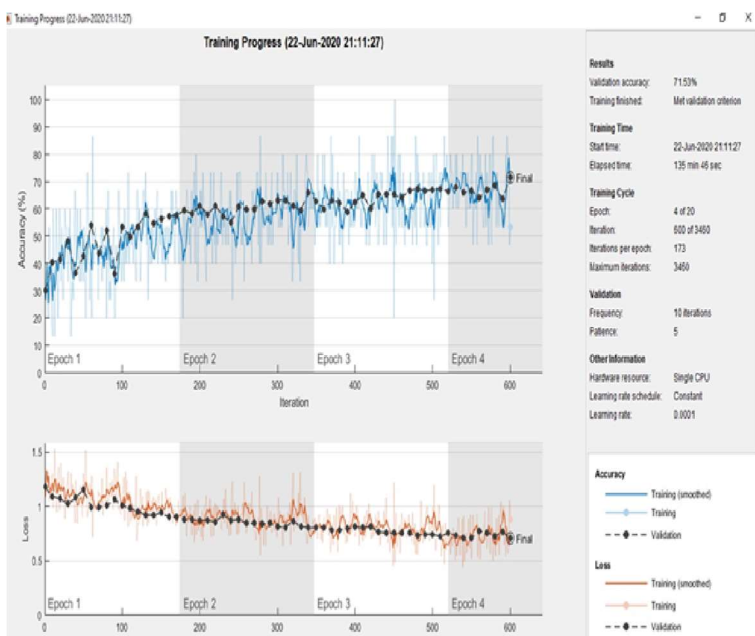

Fig.9. Optimized Trained Network

4.3 Results

The results obtained for the proposed work have been discussed in this section. The below wavelet in fig 10 shows the exact emotion prediction with the peak values. The below graph shows the prediction of the emotion.

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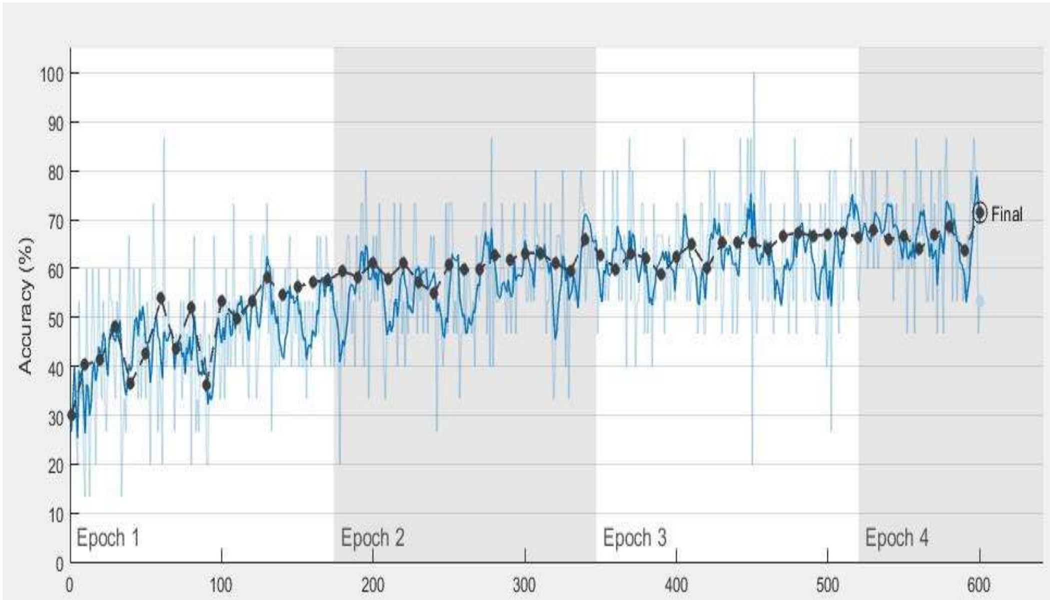

Fig.10. Accuracy Plot

The Loss curve during training is one of the most popular plots for debugging neural networks. It provides an overview of the learning process and the direction the network is learning. The loss plot for the proposed work is shown in figure 11.

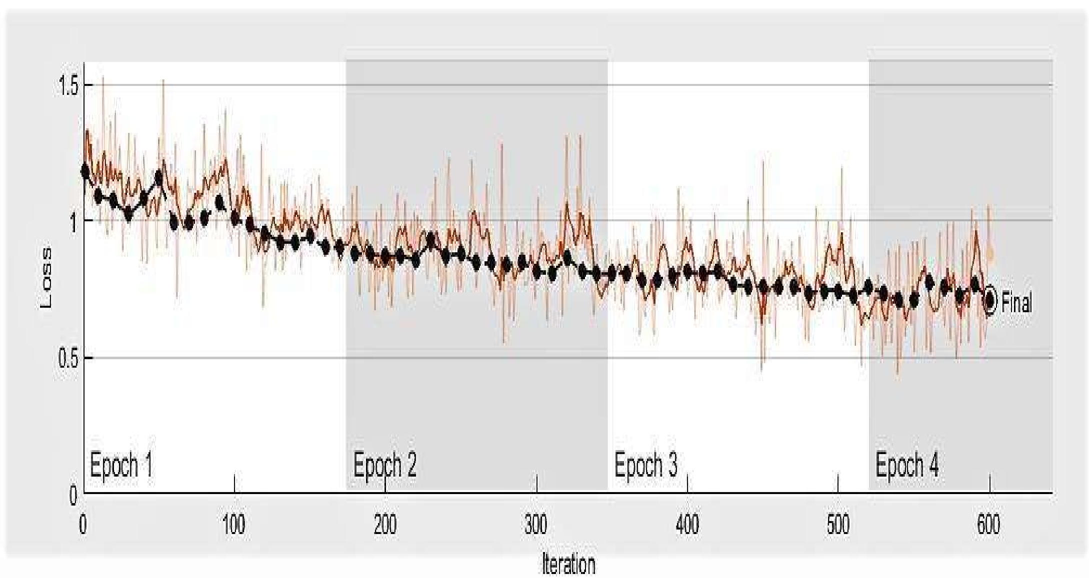

Fig.11. Loss Plot

4.4 Testing of New Signals

The new wavelet signals are tested and its output is shown in the fig 12 and 13. The final output for predicting the different

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-319

emotions using the wavelet signals as input is shown in figure 13. The trained model predicts the exact emotion very accurately.

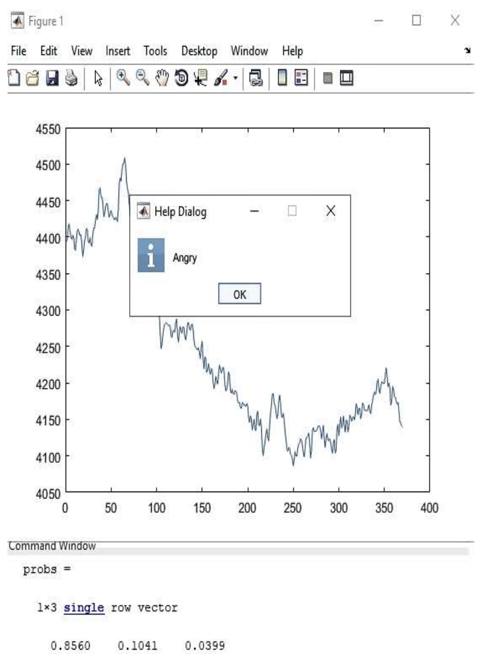

Fig 12. Testing For New Angry Signal

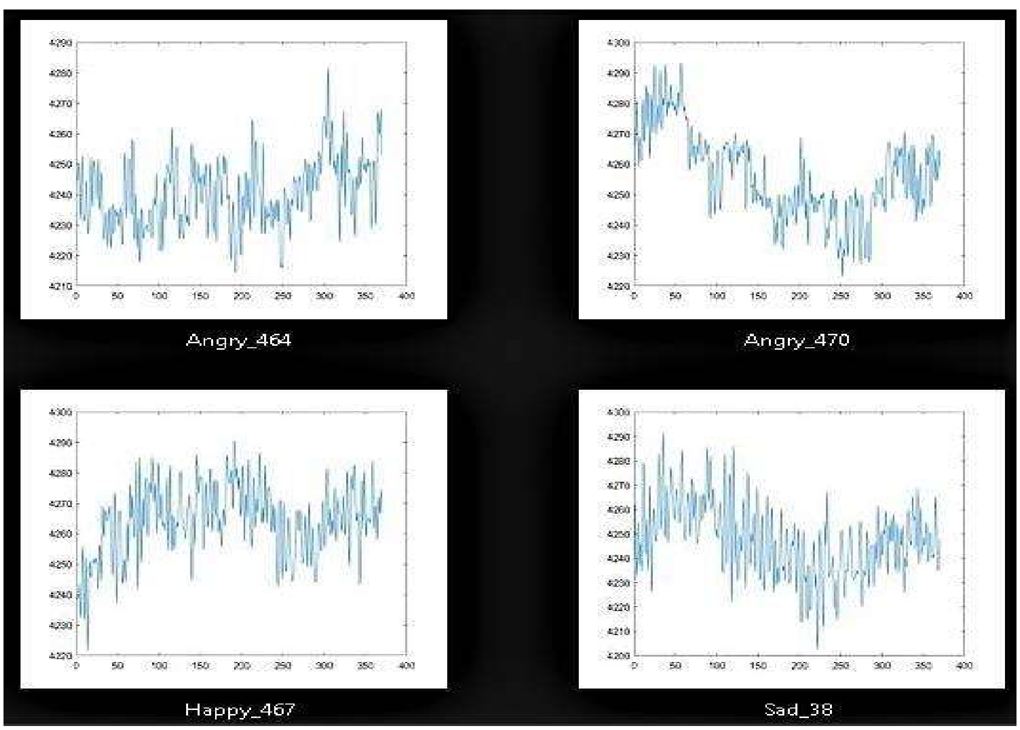

Fig. 13. Testing For New Signal Files

5. CONCLUSION AND FUTURE ENHANCEMENT

This proposed work lays the groundwork for Emotion classification using only EEG, which can aid in several medical procedures. While using images in a place or pre-processed values, even emotions can be derived instead of the generic output of valence and arousal [12]. This method will prove beneficial in the quick analysis of the EEG signals without many pre-necessities. In this, the Non-linear method is kept as a base for classifying EEG signals originating from focal and non-focal regions of the brain. The result is suitable for all types of neurophysiological applications. The proposed algorithm has high accuracy and is the most nascent method of classifying EEG signals in the field. Further work is needed for quality assurance of abnormal signals.

On the extension, Quality assurance is maintained with the varying signals that require higher accuracy. Furthur directions of research will involve: (1) acquiring all dimensional signals, such as ECG to detect direct correlation on circulation; (2) algorithms proposed to undergo consecutive analysis with the projection on different states and (3) FCNN algorithms for Classification. Adding signals like the ECG (Electrocardiogram) may limit the applicability of the algorithm, but would make it more accurate for those datasets that have those signals available.

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